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BAYESIAN METHODS FOR IMAGE SEGMENTATION (Preprint)

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14. ABSTRACT
This paper presents an introduction to Bayesian methods for image segmentation, and provides some examples of the performance of these methods. Bayesian image segmentation methods represent a class of statistical approaches to the problem of segmentation. The idea behind Bayesian techniques is to use statistical image models to incorporate prior information into the segmentation process. This is typically done by specifying a model for the observed image to be segmented and a model for the segmentation image itself. These image models are then used to create a cost function which is optimized to obtain the segmentation result. Different Bayesian segmentation schemes are distinguished by several aspects: the image models used, the optimization criterion used to obtain the cost function, and the computational approach used to perform the optimization.

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Bayesian Methods for Image Segmentation

Mary Comer, Charles A. Bouman, Marc De Graef, and Jeff P. Simmons

This paper presents an introduction to Bayesian methods for image segmentation, and provides some examples of the performance of these methods. Bayesian image segmentation methods represent a class of statistical approaches to the problem of segmentation. The idea behind Bayesian techniques is to use statistical image models to incorporate prior information into the segmentation process. This is typically done by specifying a model for the observed image to be segmented and a model for the segmentation image itself. These image models are then used to create a cost function which is optimized to obtain the segmentation result. Different Bayesian segmentation schemes are distinguished by several aspects: the image models used, the optimization criterion used to obtain the cost function, and the computational approach used to perform the optimization.

- *Image models.* Perhaps the most commonly used statistical image model is the Markov random field (MRF). This model imposes a smoothness on the segmentation, by imposing the constraint that neighboring pixels are likely to share the same classification. An MRF is often used to model the segmentation image, and sometimes is also used to model the observed image [1]. The observed image model also often incorporates a model for the noise in the imaging system. The most common model for the noise is Gaussian, although other noise models can be incorporated.

- *Estimation criteria.* There are several popular optimization criteria for Bayesian segmentation. Perhaps the most common is the *maximum a posteriori* (MAP) criterion [2]. The MAP estimate represents the most likely segmentation given an observed image, and it is obtained by maximizing a function we will refer to as the posterior likelihood function. Another criterion for Bayesian segmentation is the *maximizer of the posterior marginals* (MPM) criterion [3]. The MPM estimate is the segmentation that minimizes the expected number of misclassified pixels. A third Bayesian-type criterion for segmentation is the *minimum mean-squared error* (MMSE) estimate [1]. The MMSE estimate is the segmentation that minimizes the mean-squared error between the estimator and the true segmentation. It can be shown that the MMSE estimate represents the mean value obtained using the posterior likelihood function, as opposed to the MAP estimate, which maximizes the posterior likelihood.

- *Computational approaches.* One of the difficulties that arises in Bayesian segmentation is that the optimization of the cost function is generally nontrivial. For this reason, iterative approaches that approximate the exact solution are used. Historically, greedy algorithms [4] or Monte Carlo-based approaches [2, 3] have been used for this purpose. While greedy algorithms are fast, they sometimes give poor results, whereas the Monte Carlo approaches are slower but more accurate. More recently, graph cut methods [5] and belief propagation [6] have been proposed for Bayesian image segmentation.

1 Experimental Results

Some results showing the performance of a particular Bayesian segmentation are given in this section. The results are obtained using the EM/MPM method described in [7–9]. This method uses an MRF model for the segmentation image, a Gaussian model for the observed image, the MPM estimation criterion, and a Monte Carlo-based approach to perform the segmentation.

The image on the left in Figure 1 shows a Ti alloy. The Ti sample was forged in the β phase field, leading to large α laths surrounding large areas of β phase. On cooling, the β phase decomposed to give a mixture of fine α and β. The two different phases result in two different textures in the image; the texture classification problem seeks to assign each pixel a label according to whether it lies in an α or β phase region. The image on the right in Figure 1 shows the result of applying EM/MPM. The algorithm is sufficiently robust to allow a stack of serial section images to be segmented and reconstructed into a 3D volume, as shown in Figure 2.

Figures 3 and 4 show a sequence of images representing the growth of a silicon nanowire. These nanowires are grown from a liquid AuSi alloy [10], which appears as the darkest region in each image. The slightly lighter region growing at the edge of the AuSi region is a Si region that is formed by a nucleation process from the AuSi. The Si region is the growing nanowire, and we wish to segment the nanowire from the AuSi material and the background.

Figures 3 and 4 show Bayesian segmentations of two different nanowire sequences. In each figure, the top row shows the original sequence, the middle row shows a segmentation using a 2D version of the EM/MPM method applied to each image in the sequence independently, and the bottom row shows the result of a 3D version of EM/MPM that includes prior information about the physics of the nanowire growth process [9]. It can be seen that incorporation of the prior information greatly improves the segmentation results. This example illustrates the general principle that prior knowledge incorporated into Bayesian segmentation methods can significantly improve segmentation performance.

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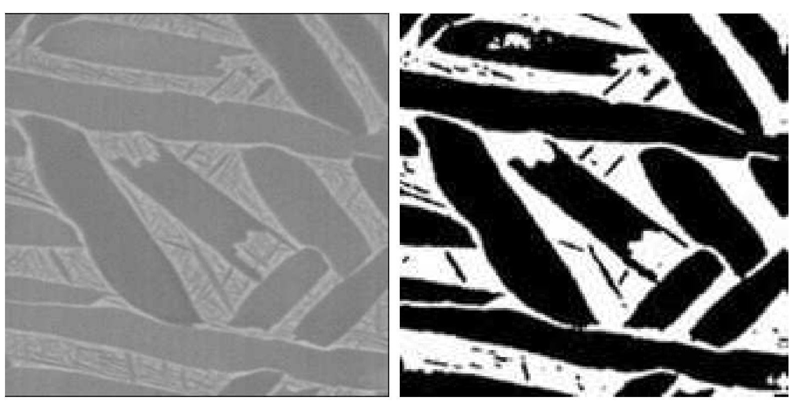

Figure 1: Original Ti alloy image (left) and segmented image (right). Image data courtesy of Prof. Hamish Fraser of Ohio State University.

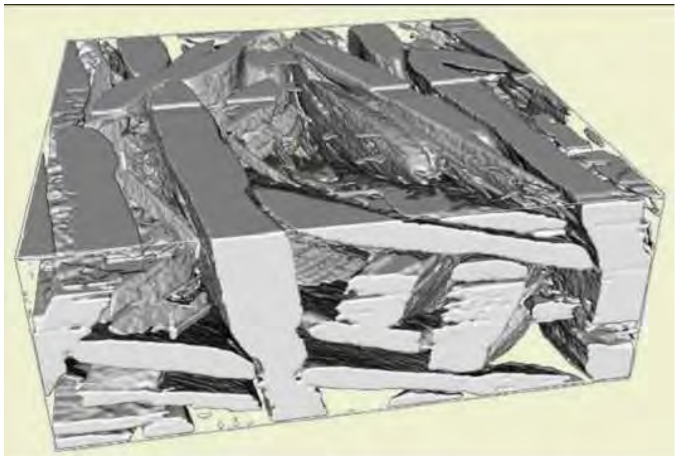

Figure 2: Segmentated 3D stack of Ti alloy images.

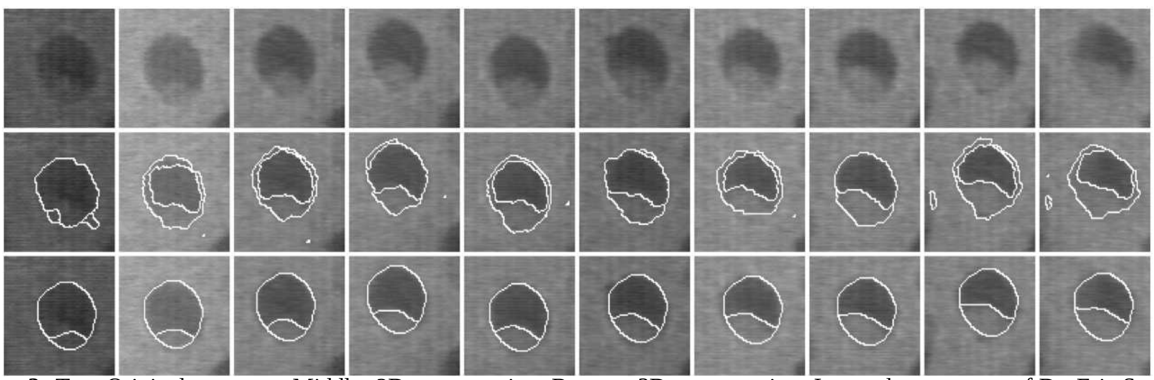

Figure 3: Top: Original sequence; Middle: 2D segmentation; Bottom: 3D segmentation. Image data courtesy of Dr. Eric Stach of Brookhaven National Laboratories.

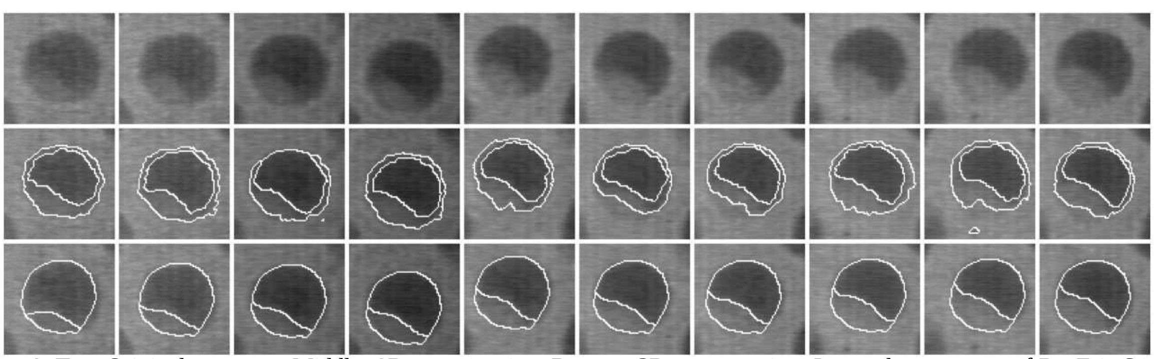

Figure 4: Top: Original sequence; Middle: 2D segmentation; Bottom: 3D segmentation. Image data courtesy of Dr. Eric Stach of Brookhaven National Laboratories.

Figure 5: Tomography figure.

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